

# Deformed Iris Recognition Using Bandpass Geometric Features and Lowpass Ordinal Features

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## Abstract

*Deformation of iris pattern caused by pupil dilation and contraction is one of the most influential intra-class variations. Most state-of-the-art iris recognition methods only focus on the description of local iris texture features. We believe that both geometric and photometric features are important to achieve a robust matching result of deformed iris images. This paper proposes to decompose iris images into lowpass and bandpass components using nonsubsampling contourlet transform (NSCT) and then extract different features. Geometric features are extracted in bandpass components based on key point detection to align deformed iris patterns. And then aligned Ordinal features are extracted in lowpass components to characterize the ordinal measures of local iris regions. Finally, key point features in bandpass components and Ordinal features in lowpass components are fused for deformed iris image matching. Extensive experiments on two challenging iris image databases namely CASIA-Iris-Lamp and ICE'2005 demonstrate that the proposed method outperforms state-of-the-art methods in deformed iris recognition.*

## 1. Introduction

Human iris between the pupil and sclera contains complex and random texture information which is highly discriminating and stable during the whole life. Iris recognition is an automatic identification method by analyzing iris patterns based on non-contact imaging of human's iris [7]. As the muscles surrounding a pupil contract or relax, the size of the pupil changes to regulate the amount of light entering into an eye. Therefore, illumination variations will cause significant changes in pupil size. In the daily illumination environment, pupil diameter usually varies from 1.5mm to 7mm [17]. As a result, the changes lead to iris deformation dramatically and introduce large intra-class difference. Thus, iris recognition under unrestricted illumina-

tion conditions is an extremely challenging problem.

There are three categories of methods to handle iris deformation. The first one is image preprocessing. Daugman [7] proposed to linearly stretch the circular iris area into a rectangle image. Yuan *et al.* [18] described the relationship of iris collagen fibers between different iris sizes by employing a meshwork model. Wei *et al.* [16] applied a Gaussian function to normalize deformation of iris texture nonlinearly. However, precise mathematical model of iris deformation does not exist. Even after image preprocessing, deformed iris images are still highly different. Thus the second kind of methods is to extract robust features. Sun *et al.* [14] made use of qualitative iris texture representation which is robust to deformation to a certain degree. Ortiz *et al.* [13] implemented dilation-aware enrollment to improve recognition accuracy. To address heavy deformation, robust matching strategies can be our third resort. Under a Bayesian model, Thornton *et al.* [15] utilized maximum a posteriori probability (MAP) parameters of training iris images for matching deformed patterns. The approach in [10] estimated iris deformation as a bunch of hidden variables and designed a graph model. Zhang *et al.* [19] showed perturbation-enhanced local and global feature fusion method for robust iris recognition. Although there are lots of deformed iris image matching methods, it remains a challenging problem and deserves further study.

In [7] [5] and [12], multi-channel filters were utilized to extract multi-scale and multi-orientation iris features. It is mentioned that discriminating features are contained in different frequency bands. Inspired by these work, we propose a novel algorithm using bandpass geometric features and lowpass Ordinal features for deformed iris image matching. Two kinds of iris features are extracted in different subbands and then fused for deformed iris image matching. In the flowchart shown in Figure 1, a normalized iris image is decomposed into lowpass and bandpass subbands by *nonsubsampling contourlet transform* (NSCT) [4] in the be-

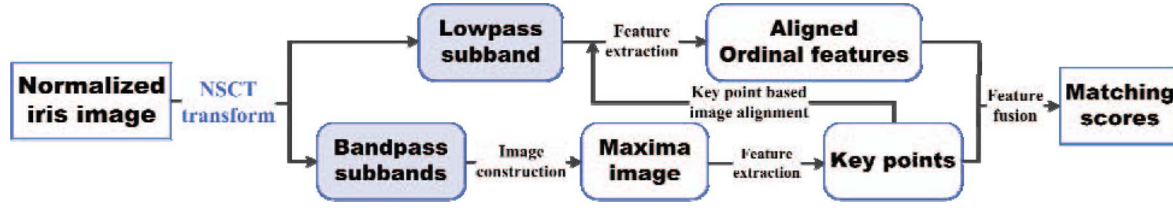


Figure 1. Flowchart of the proposed algorithm

ginning. And then key points and aligned Ordinal features are extracted in different subbands, separately. At last, two kinds of features are fused for final matching. The details of the proposed method can be seen in Section 4.1.

There are three main contributions of our work. Firstly, due to the shift-invariant, multi-scale and multi-direction properties of NSCT, smooth iris texture contours are extracted effectively. Secondly, deformed iris images are easily aligned by the locations of key points extracted from the subbands where iris texture edges are strengthened. Lastly, diverse features in different subbands are separately extracted and then fused, which can make use of various advantages of different subbands.

The remainder of this paper is organized as follows. Section 2 reviews the background of the proposed algorithm. Section 3 gives the motivation of the algorithm. The technical details of the proposed algorithm are described in Section 4. Experimental results on two challenging iris databases are presented in Section 5. Finally, Section 6 gives concluding remarks.

## 2. Background

This paper proposes to extract and fuse two sets of iris features based on *nonsubsampled contourlet transform* (NSCT) [4] which is a shift-invariant improvement of *Contourlet Transform* (CT) [8]. NSCT adopts *nonsubsampled pyramid* (NSP) structure to ensure its multi-scale property and *nonsubsampled filter banks* (NSFB) to capture directionality in images, respectively. Different from other discrete image decomposition algorithms, NSCT separates images into different subbands iteratively in an unseparated way, which means the original geometric and edge information can be fully preserved in the decomposition results. Similar to the structure of Contourlet Transform [8], we can select different kinds of nonsubsampled pyramids and nonsubsampled directional filter banks as discussed in [4].

In general, NSCT decomposition results contain lowpass and directional bandpass subbands. NSP detects edge points in an image and NSFB joints the detected edge points in the same direction together. The geometric and edge information are captured and fully preserved in directional bandpass subbands, which will be described in detail in Section 4.2. The remained image information constructs lowpass subbands, thus lowpass subbands contain less noise

and less high-frequency image information. Different from other existed image decomposition methods, the distinct advantage of NSCT is that it detects smooth boundaries successfully.

## 3. Motivation

Iris recognition accuracy is commonly affected by iris deformation caused by illumination changes, emotion, medical condition and so on. When iris images are acquired in different illumination environments, pupil dilation and contraction generate serious iris elastic deformation, which leads to large intra-class difference. As shown in Figure 2, the two iris images are both from the same class in CASIA-Iris-Lamp Database [1]. Image A and B were acquired in the bright and dark environments, respectively. Even though the iris areas are linearly normalized into rectangle images with the same size, they look highly different.



Figure 2. Deformed iris examples from the same class (This figure is better viewed in color.)

Usually, iris images are registered and recognized at different time, even by different devices. The changes of environment illumination make heavily deformed iris images ubiquitous in iris recognition so as to decrease recognition accuracy significantly. Thus in this paper we propose a deformed iris recognition method using bandpass geometric information and lowpass Ordinal features to solve this problem. This method decomposes iris images into different subbands and extracts different features based on the unique characteristics of subbands. The geometric features extracted in bandpass subbands based on key point detection are used to align deformed iris images and then alignment information is taken into account to help local Ordinal feature extraction in lowpass subbands. Furthermore, fusion of key point features and aligned Ordinal features is applied to achieve better recognition performance in the last step.

## 4. Technical Details

### 4.1. Framework of proposed method

A novel deformed iris image matching method using bandpass geometric information and lowpass Ordinal features is proposed to address deformed iris image matching problem. In our work, *nonsubsampling contourlet transform* (NSCT) is implemented to decompose normalized iris images for its multi-scale, multi-direction and shift-invariant properties. We find out that bandpass subbands contain smooth and strengthened iris texture boundaries, which makes bandpass subbands suitable to extract key points for deformed image alignment. Meanwhile, lowpass subbands contain less noise and less high-frequency information, thus they are suitable to extract local iris features.

There are four main steps in the framework of the proposed method shown in Figure 1. Firstly, normalized iris images are decomposed into lowpass and bandpass subbands by NSCT. Secondly, bandpass subbands are taken to construct maxima images and extract key points in order to align deformed iris images. Thirdly, the locations of key points are utilized for aligned Ordinal feature extraction in lowpass subbands. Finally, these two sets of features in different subbands are fused.

### 4.2. NSCT decomposition and NSCT maxima image construction

In the beginning, we decompose each normalized iris image into subbands at three different levels by *nonsubsampling contourlet transform* (NSCT). The first level stands for the lowpass subband and the other two ones represent bandpass subbands in 8 orientations, thus 1 lowpass and 16 ( $8 \times 2$ ) bandpass subbands with the same size are obtained. All the subbands are labeled as  $B_0, B_{1n}, B_{2n}$  ( $n = 1, 2, \dots, 8$ ), where  $B_0$  is the lowpass subband,  $B_{1n}, B_{2n}$  ( $n = 1, 2, \dots, 8$ ) stand for the bandpass subbands and  $n = 1, 2, \dots, 8$  means 8 orientations. After decomposition,  $B_0$  appears more smooth than the original image for it only contains lowpass information, while the directional boundaries are mostly preserved in  $B_{1n}$  and  $B_{2n}$  ( $n = 1, 2, \dots, 8$ ).

When a certain iris image is decomposed by NSCT, to eliminate noise and integrate the directional boundary information in different bandpass subbands, a maxima image is constructed based on the decomposition results. The process of maxima image construction is described as follows:

*Step 1:* The difference between two subbands is computed in each direction.  $D_n = B_{1n} - B_{2n}$  ( $n = 1, 2, \dots, 8$ ), where  $D_n$  is named as 'difference image' in the  $n^{th}$  orientation. Thus we can get 8 difference images.

*Step 2:* At each pixel, we combine the maximum magnitude from the 8 difference images as a new one defined as 'NSCT maxima image'.  $M(i, j) = \max(D_n(i, j))$ , where  $M$  is the maxima image and  $(i, j)$  is the pixel coordinate.

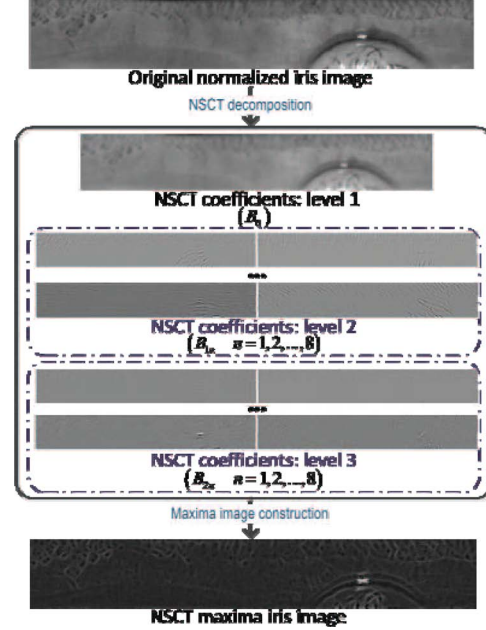


Figure 3. NSCT maxima iris image construction

### 4.3. Key point extraction

Bandpass subbands are utilized to eliminate noise and enhance boundaries of iris texture when we constructed maxima images, which makes maxima images more suitable to extract key points than corresponding original images. Thus we can align two images by locating and matching key points in maxima images more accurately.

In our work, we select Speeded Up Robust Features (SURF) [3] for key point extraction and matching. SURF is widely used to detect and match scale and rotation invariant interest points. In contrast to other existed key point matching algorithms (e.g. [9] [11]), SURF detects more scale and shift invariant key points faster and more accurately.

At the key point extraction stage, firstly locations and scales of key points are selected based on Hessian matrix and integral images due to their low time cost and high accuracy. Then a 64-dimension feature for each key point is computed with the help of main orientation and gradient in scale space. SURF points are selected by Blob-like feature detector efficiently later. Besides, the dominant orientations and descriptor of SURF points can be determined by Haar wavelet responses in point locations. Finally, when two maxima images (no matter whether they are from the same class or not) need to be aligned, Euclidean distance is taken to measure the similarity of key points from them.

By taking a real example in our experiments shown in Figure 4, we find 55 pairs of effective SURF key points between two normalized iris images. While 96 pairs of effective SURF key points are located between two maxima

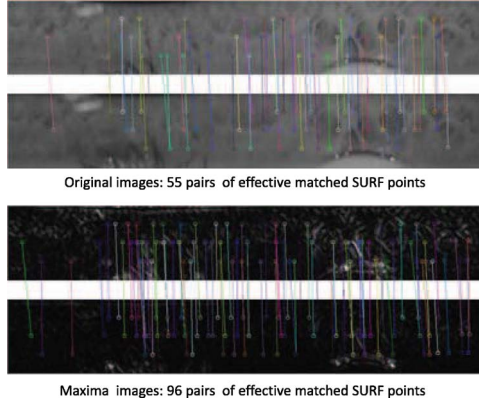


Figure 4. SURF point extraction and matching

images of theirs. This example illustrates that maxima images are more suitable to locate key points and align images. With the benefits of key points in maxima images, deformed iris images are easily aligned, which pave the way for local feature extraction and matching in the next step.

#### 4.4. Aligned Ordinal feature extraction and fusion

*Ordinal measures* (OM) come from an intuitive idea in our daily life - qualitative description. This idea can also be applied in feature extraction. We only focus on the qualitative relationship between two pixels, such as whether one is brighter or darker than another one. If one pixel is brighter than another one, it is encoded as '1'. Otherwise, it is encoded as '0'. The binary codes are applied to present the qualitative relationship instead of the real value of the two ones. Sun *et al.* [14] take advantages of Ordinal measures to encode the qualitative relationship between different block regions in iris images. Each iris image can be encoded into a sequence of binary iris code to describe the qualitative difference between different image blocks from the same iris image. Ordinal measures represent micro structures and pixel value variance in a distinctive way. Meanwhile, due to the unique idea of qualitative presentation, Ordinal measures are robust to illumination changes, noise, etc.

In this paper, multi-lobe differential filters (MLDF) are applied to extract Ordinal features of iris images. A Gaussian kernel is taken as the basic element of MLDF [14], which is expressed as

$$\text{MLDF} = C_m \sum_{i=1}^{N_m} \frac{1}{\sqrt{2\pi}\delta_{mi}} \exp \left[ \frac{-(X-\mu_{mi})^2}{2\delta_{mi}^2} \right] - C_n \sum_{j=1}^{N_n} \frac{1}{\sqrt{2\pi}\delta_{ni}} \exp \left[ \frac{-(X-\mu_{nj})^2}{2\delta_{nj}^2} \right] \quad (1)$$

where  $\mu$  and  $\delta$  describe the size of each lobe.  $N_m$  and  $N_n$  stand for the numbers of positive and negative lobes, respectively. And  $C_m N_m = C_n N_n$  is necessary to ensure the zero sum of MLDF.

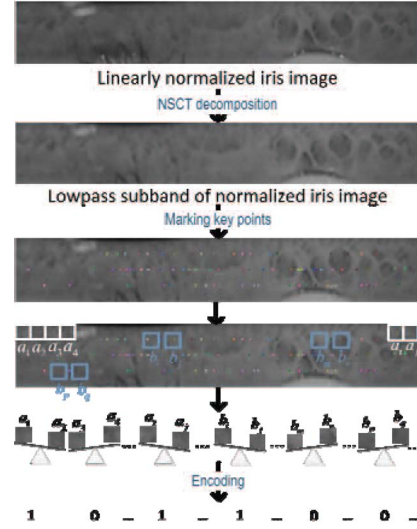


Figure 5. Aligned Ordinal feature extraction in lowpass subbands

Figure 5 shows the process of aligned Ordinal features extraction in lowpass subbands. To align a deformed iris image, SURF key points have been extracted and matched in the maxima images constructed by bandpass subbands and the locations of theirs are utilized to determine where to extract Ordinal features in lowpass subbands. In Figure 5, each colored '\*' means that there is a matched SURF key point at the same location in the maxima image. And the regions labeled as ...,  $b_i, b_j, b_m, b_n, b_p, b_q, \dots$ , which are with key points at the centers, stand for the feature extraction areas around key points. While in the regions where does not exist any key point, we label them as  $a_1, a_2, a_3, a_4, \dots, a_i, a_j, \dots$ , and use the regular location and step size for Ordinal feature extraction. For we apply the locations of key points to fix positions of feature extraction, the extracted Ordinal features are called as aligned features. After aligned Ordinal feature extraction, the lowpass subband of each iris image can be easily encoded into a sequence of binary iris codes. The measurement of Hamming distance (HD) between two iris codes is taken to describe the dissimilarity of these ones.

The locations of extracted SURF key points are used to align deformed iris images, while the features of them are also fused with aligned Ordinal features. Euclidean distance is taken to measure the similarity of matched key points from different iris images. Score level fusion of aligned Ordinal features and SURF features is utilized in our work. The final matching score of two images is

$$S(p, q) = S_{OM}(p, q) + \lambda \times S_{SURF}(p, q) \quad (2)$$

where  $p$  and  $q$  stand for two different normalized iris images.  $S_{OM}(p, q)$  is the Hamming distance between aligned Ordinal features of  $p$  and  $q$ , while  $S_{SURF}(p, q)$  is Euclidean distance between SURF features of them.  $\lambda$  is a weight

value to determine the relative importance of two kinds of features.

## 5. Experiments

### 5.1. Databases

The two iris databases used in this section for algorithm evaluation are CASIA-Iris-Lamp [1] and ICE'2005 databases [2].

The first one is CASIA-Iris-Lamp [1], which will be abbreviated as Lamp in the following. There are more than 800 classes and each class contains about 20 images. A lamp was turn on/off when iris images were acquired, thus heavy iris deformation was introduced into the database. The ratio of pupil radius to iris radius varies from 0.19 to 0.67 in this database.

The second one is ICE'2005 iris database [2], which will be abbreviated as ICE in the following. National Institute of Standards and Technology (NIST) released this database which contains 2953 images from 132 subjects. Most iris images from this database are low-quality, for instance, defocus, occlusion by eyelashes and eyelids, deformation and so on.

### 5.2. Experimental results

To evaluate the performance of the proposed method, we compared it with two state-of-the-art iris recognition algorithms on the Lamp and ICE databases. Two compared algorithms are both self-implemented and choose the basic parameters. All the iris images from the datasets are linearly normalized [6]. In each method, we applied one-to-one matching, which means there is only one gallery image and one probe image for each matching. The first compared method is Gabor wavelet filtering by classification with Hamming Distance [6]. In this method, normalized iris images are encoded into binary iris codes after being filtered by Gabor wavelet of different scales and orientations. The dissimilarity of two images is defined as the Hamming Distance between their codes. The second compared method is Ordinal Measures [14]. Two-lobe and tri-lobe Ordinal filters are utilized to extract iris features. And then score level fusion of two sets of features is applied. Similarly, Hamming Distance is used to measure the dissimilarity of two iris images.

Equal Error Rate (EER) and Discriminating Index (DI) [7] are taken to evaluate performance of the proposed method. EER is the value where false accept rate (FAR) and false reject rate (FRR) are equal. DI is computed as Equation 3, where  $m_1$  and  $m_2$  are two means of intra-class and inter-class distributions, and variances of the two distributions are  $\delta_1^2$  and  $\delta_2^2$ . Recognition results, EER and DI, on the two databases are shown in Table 1 and Table 2, respectively. Besides, the entire ROC curves on the two databases

are shown in Figure 6 and Figure 7.

$$DI = \frac{|m_1 - m_2|}{\sqrt{(\delta_1^2 + \delta_2^2)/2}} \quad (3)$$

Table 1. Experimental results on the Lamp database [1]

Method	Equal Error Rate (%)	Discriminating Index
Gabor filtering	12.81	2.0273
Ordinal Measures	2.94	3.5571
Proposed	2.05	5.2625

Table 2. Experimental results on the ICE database [2]

Method	Equal Error Rate (%)	Discriminating Index
Gabor filtering	8.66	2.5074
Ordinal Measures	0.80	5.3533
Proposed	0.61	5.8968

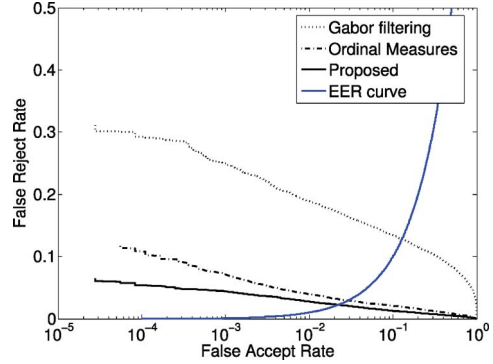


Figure 6. ROC curves on the Lamp database [1]

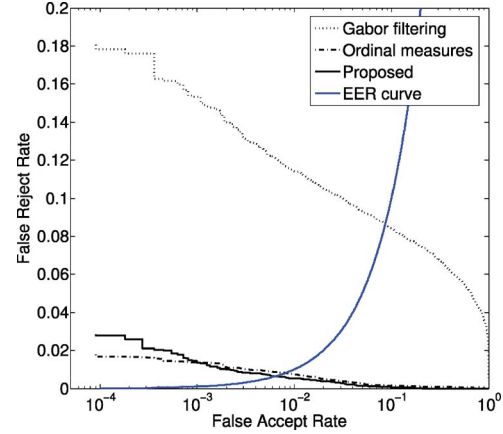


Figure 7. ROC curves on the ICE database [2]

### 5.3. Discussions

From the two tables and two figures shown in Section 5.2, we see that the proposed method is more robust

to iris deformation compared with other two methods. In our work, we select NSCT lowpass subbands rather than bandpass subbands to extract local Ordinal features. Although the lowpass subbands contain little high-frequency image information, it almost does not affect Ordinal feature extraction. Besides, the lowpass subbands contain less noise, which is positive to feature extraction and matching. At the same time, due to the characteristics of NSCT bandpass subbands, the key points are stable and suitable for deformed image alignment.

Although the experimental results are encouraging, the problem of deformed iris image matching has not been totally solved. In our work, we align deformed iris images by applying SURF points, the amount of which is actually limited, thus the deformed iris images can not be perfectly aligned. Meanwhile, occlusions of eyelid and eyelashes also make negative influence on the alignment.

## 6. Conclusions

We have proposed a novel deformed iris recognition method using bandpass geometric features and lowpass Ordinal features. Four main steps are taken in this method. Firstly, normalized iris images are decomposed into lowpass and bandpass subbands by *nonsubsampled contourlet transform* (NSCT). Secondly, bandpass subbands are utilized to construct maxima images to extract key points. The locations of those points are employed for aligned Ordinal features extraction in lowpass subbands. Finally, the matching scores obtained by aligned local features and key point features are fused.

The proposed algorithm makes full use of the shift-invariant, multi-scale and multi-direction properties of non-subsampled contourlet transform efficiently. Meanwhile, it extracts and fuses different features in different subbands to take fully advantages of subbands. This algorithm is robust to deformation, noise and so on. The experimental results have shown that the proposed method is an effective approach which can reduce the error rates of deformed iris recognition. Since iris deformation is an important issue in iris recognition, we will continue to focus on deformed pattern matching in the future.

## 7. Acknowledgement

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